The European Federation of Organisations for Medical Physics (EFOMP) White Paper : Big data and deep learning in medical imaging and in relation to medical physics profession

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Editorial

The European Federation of Organisations for Medical Physics (EFOMP) White Paper: Big data and deep learning in medical imaging and in relation to medical physics profession

ABSTRACT

Big data and deep learning will profoundly change various areas of professions and research in the future. This will also happen in medicine and medical imaging in particular. As medical physicists, we should pursue beyond the concept of technical quality to extend our methodology and competence towards measuring and optimising the diagnostic value in terms of how it is connected to care outcome. Functional implementation of such methodology requires data processing utilities starting from data collection and management and culminating in the data analysis methods. Data quality control and validation are prerequisites for the deep learning application in order to provide reliable further analysis, classification, interpretation, probabilistic and predictive modelling from the vast heterogeneous big data. Challenges in practical data analytics relate to both horizontal and longitudinal analysis aspects. Quantitative aspects of data validation, quality control, physically meaningful measures, parameter connections and system modelling for the future artificial intelligence (AI) methods are positioned firmly in the field of Medical Physics profession. It is our interest to ensure that our professional education, continuous training and competence will follow this significant global development.

1. Introduction

The remarkable increases in data volume, variety, and velocity (speed of data processing), collectively called the '3 V's of big data', present vast opportunities to achieve insights, derive knowledge, and stimulate new discoveries that will result in improved patient outcomes, reduced costs, and accelerated biomedical advances. It is estimated that a total of 2.5 quintillion (10^{18}) bytes of data were generated every day in 2012 alone, and that as much data is now created in just 2 days as was accumulated from the beginning of civilization until the year 2003 [1]. Big data can be harnessed to promote new applications raising from clinical research studies and implement those in the real-world scenarios where population heterogeneity may create challenges for traditional approaches. It may allow new possibilities for early diagnoses and more effective treatments and precision medicine by enabling patient stratification which is a key task when pursuing personalized healthcare [2]. Researchers have already studied these new methods in healthcare with encouraging results in automated image analysis tasks [3], and in detecting specific pathologies and diseases [4,5].

Artificial intelligence (AI) originally referred to an area of science where machines performed tasks which would typically require human intelligence [6]. Further on, machine learning (ML) can be seen as a subset of AI methodology which seeks to derive data-driven decisions by using models built from large-scale training data [7]. Therefore, ML may enable outcome prediction on new data purely based on earlier training data without explicit previous programming or expert-defined feature models. In other words, it learns by generalising results and patterns from experience [8]. ML algorithms can be divided into supervised, unsupervised, reinforced and transfer learning depending of the training method [9]. In supervised learning, the training inputs are given together with known (labeled) ground-truth or target values in order to guide the building of the ML outcome prediction model. In unsupervised learning, the algorithm seeks the patterns in the given training data without labeled outputs. Reinforced learning approaches adjust the prediction model along the way by using feedback to steer the long-term goal of the prediction. Finally, transfer learning may be applied when there is only a small amount of training data from the actual task scenario. Then, a pre-trained algorithm from another prediction task may be used for the new task, by performing an additional training part to fine-tune the earlier outcome prediction model to be more suitable for a new task. Moving along the hierarchy of ML methods, deep learning (DL) forms a subset of ML where the abstraction level of the data is increased gradually in various cascaded signal processing layers in a neural network architecture, allowing higher level features to be created from the original input data for the final prediction task. When combined with representative and large enough training data, the DL methods, especially convolutional neural networks (CNN), have proven to be highly efficient and more accurate than earlier AI methods e.g. for image classification tasks [10]. The success of DL can be traced to its architecture, utilisation of high computing power on graphics processing units (GPU) based platforms, and a large amount of training data [8]. An extensive review by Litjens 2017 covered more than 300 papers in this field, showing how DL solutions are spreading into every aspect of radiological image analysis. Furthermore, this development has occurred very quickly as most of the studies were published only recently, in 2016 or 2017 [11,8].

A number of DL architectures has been applied to medical image analysis. The first studies in this area were using pre-trained CNNs mainly for feature extraction tasks. The possibility to simply download already existing pre-trained networks has also helped to adapt them to new medical image applications. Furthermore, previously used feature-based methods could be elaborated further on deep networks with more extended set of features [11,12]. DL methods have already been used successfully on various radiological imaging modalities such as mammography [13,14], computed tomography (CT) [15] and magnetic

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resonance imaging [16,17]. Also techniques outside traditional medical imaging with static data, such as signal distributions from magneto-encephalography and electro-encephalography, have been targeted with new deep learning platforms [18,19]. During the past few years, the use of DL methods has been developed further to the direction of end-to-end trained CNNs which have become the most promising approach for medical image interpretation. While envisioning larger scope applications in the clinical environment, such CNNs could be further integrated into conventional diagnostic processes to upgrade their existing methodologies [11].

DL methods can be used generically for a large number of tasks in medical imaging, also covering image production steps such as image reconstruction. Therefore, these techniques and applications will not only have a potential impact in image analysis, but in the entire medical imaging and healthcare [20,21,11,12,22,23,24,25,8,26]. The main challenge in the clinical applications of this area is the detection of tissue or organ abnormality. The algorithms must be able to detect the lesions accurately and precisely, in order to provide consistent clinical performance. Various clinical trials and medical imaging analysis research studies will be needed to validate these learning algorithmic methods.

At a general level, AI applications in healthcare can work in synergy with the exponential growth of healthcare data to create insights for better-informed decisions. These should ultimately lead to improved quality and safety of healthcare, and reduction of costs by enabling care to be more preventive and personalized. Discovering associations and identifying patterns and trends within the healthcare data can help to improve care processes, save lives, and lower the long-term costs. The means to utilise real-time analytics against a high volume of heterogeneous data (including structured, unstructured, and semi-structured) on-line and across all specialties would revolutionize healthcare [2,24].

2. Need for deep learning approach in medical imaging

ML has been used increasingly in radiology because typical imaging objects such as lesions and organs presented in medical images are in most occasions far too complex to be represented reliably by a certain simple equation or hand-crafted model. Such simple models, and the simple features calculated from them, cannot generally provide the discrimination power to reliably detect and classify objects of interest in individual patient images with variable indications [27]. Since there is large individual and case-specific variability of normal tissue and lesion representation in radiological images (including variability in size, shape, location, position, edge profile, contrast, texture and noise in target and background), robust analysis method (with inclusion of a large amount of features from a large amount of heterogeneous data) is a fundamental requirement. Consequently, such analysis task cannot be successfully simplified or confined by any traditional analytical or rule-based approach [11,27].

The large number of parameters involved in the ML methods has to be determined directly from the data instead of manual operation. In order to find the most relevant high-level abstraction of the imaging task metrics, DL process will go through several layer transformations of the data [28,2,8]. These layered transformations include also several non-linear phases and the overall process can be applied to an end-to-end image analysis – from images used as an input to the final result (e.g. classification task). Accordingly, it may also avoid errors caused by the conventional feature extraction and segmentation methods, which face challenges and inaccuracies for subtle or complex object detection and classification from clinical data [27,2,8].

3. Link to radiological optimisation, quality assurance and patient-specific dosimetry

New radiological imaging technology, reconstruction and post-processing techniques provide new and mostly non-linear image output. An example of this development is the iterative reconstruction in CT, as compared to the traditional filtered back-projection reconstruction method. These new methods also call for more versatile description of clinically relevant image quality, preferably by objective quantification to enable consistent method for image analysis [29].

Improvement in radiological optimisation requires patient-specific and indication-specific adjustment of imaging parameters and image analysis methods. One size and purpose simply does not fit all patients and applications. This is particularly important in high radiation dose modalities such as CT or fluoroscopy used in interventional therapeutic procedures.

Both of these aspects – nonlinearity and patient/indication specificity – aim to improve diagnostic information content and representation of task-specific image features in radiology.

However, what is actually most relevant and more comprehensive, is the effectiveness of the diagnostics for the clinical outcome. Therefore, on a broader context, we need to develop methods to measure this effectiveness. To do that, objective, quantitative and measurable connections from diagnostic optimisation parameters to clinical outcome parameters need to be developed.

The required metrics involve combining several types of data together for more comprehensive analysis, as also described in a recent publication from an international summit [30] describing the optimisation process. Accordingly, the comprehensive optimisation process should include the combined risk factors from clinical aspects and radiation dose. To provide effective and patient specific risk – or benefit – assessment, the radiation risk models and clinical image quality definition could be determined further by utilising clinical data channels such as previous radiology findings, lab results, genetic data and other clinical information [30]. DL methods are prerequisites for this kind of data analysis due to inherent non-linearity of the problem and large amount of heterogeneous data which is not equitable by traditional methods [11,27].

In addition to the optimisation, also quality assurance (QA) and patient-specific dosimetry would benefit and evolve by utilising AI methods. As the QA pursues higher efficacy through more explicit connections to diagnostic process and vendor-specific technical parameters, the AI approach may provide means to utilise this increasing pool of data for improved usage, performance monitoring, cost efficiency and access of the imaging equipment [2,4]. Furthermore, extending from standard dosimetry parameters to include image data and clinical parameters has significant potential to boost accuracy and robustness of patient-specific dosimetry which is pivotal for future patient and indication-specific optimisation process. There is already an initial published study aiming towards DL-based organ dosimetry [31]. Still, literature is scarce regarding the use of these algorithms in dosimetry or QA. Recently, Valdes et al. 2017 as well as Interian et al. 2018 explored the use of such algorithms in intensity-modulated radiation therapy QA with promising results [32,33].

4. Challenges in deep learning AI

The healthcare information technology environment and its processes have not evolved in the same open manner as the Internet. On the contrary, our PACS (Picture archiving and communication system) and EMR (electronic medical record) in hospitals and clinics are in most cases operating independently of each other and their data is maintained in separate silos [34]. Even within a certain medical discipline and department in a single hospital, the essential information is in many cases “hidden” in a separate system due to the lack of procedures for integrating data and communicating findings more comprehensively. Therefore, there are still great challenges to leverage the full potential of the data which actually may already exist, but without effective utilisation in larger context [2]. This potential may be true also for the sole use of medical image data. The large coverage, accuracy and volume provided by the current 3D medical imaging modalities includes vast amount of phenotype data from the patients which can be used to extract relevant biomarkers even linked to mortality [35].

Efficient access to the data for the ML methods calls for minimized bureaucracy but also secured patient confidentiality and privacy according to ethical and legislative requirements. Related challenges involve creation of privacy, security and layered access to protected non-de-identified or partially de-identified health information. This also includes ethical challenges related to the specific patient consent to data sharing. To meet these challenges, data privacy algorithms conforming to human subject protection legislation and approvable by institutional review boards have to be created and factored into development of data research infrastructures. This kind of fundamental technical, safety, legislative and process related development of technologies and infrastructures will require inter-organisational and multidisciplinary cooperation among governmental agencies, scientists, healthcare providers, companies and other interested parties [2].

In addition to the previously stated medico-legal and ethical challenges, the technical challenges in the utilisation of big data with ML methods are related to the data itself. Big imaging and dose data may contain a considerable amount of imprecise, incomplete or ambiguous data. Unreliable data collection systems, disorganized data management, human errors, biases, software bugs can lead to inaccurate results and wrong decisions. Even though the ML methods may be intrinsically robust to various uncertainties in the input data, there is still great need for data validation and standardisation. If and when there are uncertainties in the data, the knowledge of such uncertainties in various data channels will help in the analysis tasks by defining the confidence of typical data values and the outliers. In other words, more accurately and precisely defined input data can lead to more effective outcome. The need for validation is emphasized in the correctly defined outcome values and image annotations in the training and validation data when developing and verifying new ML methods for clinical use.

In summary, two main challenges can be clearly observed in acquiring the required training data for DL based AI and medical image analysis: 1) gaining access to medical archives, located in closed proprietary databases in hospitals with privacy regulations impeding distribution and access to the data, and 2) obtaining validated and annotated image data in a systematic fashion (data values themselves, heterogeneity of the data sources, and provision of data labeling) [11,2,36,8,26].

5. How can medical physicists start to prepare?

An immense progress in technology offered by recent AI methods opens new horizons in the field of medical imaging and in understanding and management of diseases. New methods of early diagnosis and treatment which can be tailored to each particular individual and specific clinical problem are approaching fast. In medical imaging, these methods are referred to as radiomics, defined as 'the high-throughput mining of quantitative image features from standard-of-care medical imaging that enables data to be extracted and applied within clinical-decision support systems to improve diagnostic, prognostic, and predictive accuracy' [37]. These and other AI-based methods need a multidisciplinary approach. Medical physicists should develop new AI techniques for medical imaging and cooperate with clinicians to translate research results into clinical practice [38].

Although AI may replace several routine tasks related to medical physicist work in the future, as discussed in recent point/counterpoint publications [39,40], it will also generate new ones [41]. There is a transition in our role towards more comprehensive expertise and clinically relevant impact from our knowledge [42,43]. It means a change of focus from equipment to operation; from quality to consistency of quality, from testing performance to estimating outcome – and doing this with objective, standardisable and quantitative methods [44]. This general professional trend will hold regardless of AI methods but the development and implementation of AI will advance this trend in new directions. Big data validation and data QA in medical imaging will soon become a critical issue in research and everyday clinical practice. Therefore, medical physicists should develop big data QA programs in their field of expertise to assess data veracity and validity using metrics such as data completeness, data accuracy, data correctness, data consistency and perform data cleaning activities. Each channel of quantitative data must be properly calibrated and associated with the valid physical quantity and unit prefix to provide correct input to the following analysis. Understanding of uncertainties in quantitative values, including estimates of accuracy and precision, forms a prerequisite for this process. These foundations of data fidelity are clearly within medical physicist professional area and our field of knowledge.

In order to secure our field of knowledge also in the future, medical physicists must be prepared for facing the AI technology by updating our training and education programs [40,41]. Currently there is a lack of courses, workshops and other scientific events that can educate medical physicists efficiently on issues related to big data, DL, ML, or on AI in general. Medical Physics academic or educational programs (such as bachelor, master or doctorate) should include these new fields in their core curriculum. Within the scope of EFOMP, this kind of education could be provided by the ESMPE (European School of Medical Physics Expert) course modules which are organized regularly in order to provide basic and advanced training for medical physicists on an international level.

The changes induced by the technological transformation also effect the collaboration and working culture between professions. The next generation of medical physicists must be prepared to work in an increasingly multidisciplinary clinical environment in which professional boundaries and borders between diagnostics and treatment processes are increasingly blurred and overlapping. In that mixed field of expertise, medical physicists could be the connecting point among different professionals (e.g. clinicians, bio-engineers and biomedical informatics specialists) provided they are well educated and carefully trained in the revised processes of translation of all these potential benefits of AI into clinical practice. The need for specialised professional knowledge will not disappear. Thorough medical physics expertise must meet with clinical knowledge of medical doctors and radiologists, and combine with skills of computer scientists. The role of computer scientists to provide expertise on big data architectures, implementations and adaptation of new IT services to support AI applications will be a prominent part of this collaboration. This combination of knowledge is essential to build capabilities to work with the mix of healthcare processes, medical technology and increasing availability of healthcare data. Our community should be prepared to meet the new challenges and opportunities and to take a prominent role in this new wave of the fourth industrial revolution extending well beyond medical physics and healthcare [40,41].

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